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(54) Title: SUPPLY CHAIN DEMAND FORECASTING AND PLANNING

(57) Abstract: Disclosed herein are systems and methods for demand forecasting that enable multiple-scenario comparisons and analyses by letting users create forecasts from multiple history streams (for example, shipments data, point-of-sale data, customer order data, return data, etc.) with various alternative forecast algorithm theories. The multiple model framework of the present invention enables users to compare statistical algorithms paired with various history streams (collectively referred to as "models") so as to run various simulations and evaluate which model will provide the best forecast for a particular product in a given market. Once the user has decided upon which model it will use, it can publish forecast information provided by that model for use by its organization (such as by a downstream supply planning program). Embodiments of the present invention provide a system and method whereby appropriate demand responses can be dynamically forecasted whenever given events occur, such as when a competitor lowers the price on a particular product (such as for a promotion), or when the user's company is launching new sales and marketing campaigns. Preferred embodiments of the present invention use an automatic tuning feature to assist users in determining optimal parameter settings for a given forecasting algorithm to produce the best possible forecasting model.

## Supply Chain Demand Forecasting and Planning

### CROSS REFERENCE TO RELATED APPLICATION

This application claims priority from U.S.
5    Provisional Patent Application Serial No. 60/243,425,
filed October 27, 2000, the disclosure of which is hereby
incorporated by reference in its entirety.

### FIELD OF THE INVENTION

10    The present invention pertains to systems and
methods for supply chain planning and demand forecasting.
In particular, the present invention pertains to systems
and methods for proactively predicting demand across
multiple levels of the supply chain so as to avoid costly
15   mismatches of demand and supply.

### BACKGROUND OF THE INVENTION

As is appreciated by those familiar with the art,
mismatches of demand and supply are costly to sellers in
a competitive market because such mismatches often result
in missed sales opportunities, lost profits, excessive
20   expediting costs, lost market share, and poor customer
service.  To maximize sales and marketing effectiveness,
companies must accurately predict future customer demand
and use this information to drive their business
operations from manufacturing to operations to
25   distribution.  This need for accurate predictions of
demand is especially important for those involved in e-
business due to the ease with which buyers can find
alternative sellers that can satisfy their demand.

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In the manufacturing and distributing industries, supplying products in response to the current level of customer demand with a minimum of overstocking reduces stocking costs and distribution expenses and thus leads

5   to a reduction of the sales unit price of products. Typically, this also leads to an enhancement of profit margins. It is therefore necessary for sellers to forecast product demand precisely such that they then can determine a sales plan, production plan, and distribution

10  plan according to an accurate forecast of the demand trend of customers.

Conventional methods of forecasting demand by analyzing the trend of past sales results are performed with the goal of the forecaster being to apply the most

15  accurate statistical analysis techniques and econometric modeling to provide the most accurate forecast possible. In these conventional methods, time series forecasting is performed which develops and uses various forecasting algorithms that attempt to describe the knowledge of the

20  business and fluctuation trend of sales results as evidenced by past history in the form of a rule. Developing such forecasting algorithms (as well as computerized systems for utilizing such algorithms) is typically a labor-intensive task.

25      Unfortunately, however, it is common for product demand trends to change in a short lifecycle. When this is the case, the data used in providing a forecast rapidly becomes old and the precision of forecasting lowers. Therefore, in order to keep a high precision in

30  forecasting, algorithms (and historic data points used to

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generate those algorithms) must be maintained on an
ongoing basis as well as be able to adjust their
forecasts relatively easily.

5       In addition to the difficulty in computing business
demand in general is the complexity introduced by
different periodic demand patterns in certain industries
based upon day of the week, seasons of the year, or other
recurring events.  For example, in certain industries,
such as the restaurant or retail industries, foot
10     traffic, product preferences and sales volume vary
according to day of the week.  Similarly, predictable
seasonal, annual, and/or periodic fluctuations in product
demand are present to some extent in many industries. In
addition, non-periodic events promotional programs, local
15     events, holidays, and the like, all alter the demand
levels faced by a business.  An accurate forecast of
demand must be able to accommodate these periodic and
non-periodic effects on demand level.  Unfortunately, the
complexity of formulating a single algorithm for doing so
20     accurately has traditionally relegated businesses to
making educated guesses regarding what type of demand to
expect based upon their experience and records regarding
past business demand.  As one might expect, as businesses
become larger and more complex, making such predictions
25     becomes more problematic and risky.  Further, it is
unpractical, if not impossible, for a human being to
calculate and predict fluctuations in business demand on
a more frequent basis (such as hourly or even daily) even
though it may be desirable to do so.

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Therefore, since one of the more important issues encountered in production planning stems from the uncertainties associated with future demand for products, a vast volume of literature and efforts within the

5    industry has attempted to address this issue. Presently, however, production, materials and transportation planning based upon forecasted demand still presents a significant challenge. While there have been many studies in the demand planning theory area, the advances

10   achieved thus far are either based upon oversimplified assumptions or alternatively are computationally infeasible for real world application. Thus, heretofore there has not been developed a flexible yet substantially automated manner by which sellers in a competitive market

15   can satisfy their demand forecasting needs.

By way of example, U.S. Patent Application No. 6,049,742 to Milne et al. discloses a computer software tool for comparing projected supply planning decisions with expected demand profiles. The computer system

20   disclosed by Milne provides routines that compare projected supply with actual experienced demand to help the user of the software tool to configure it to best meet their business's requirements. Unfortunately, like most known demand forecasting methodologies, Milne is

25   inflexible in that it does not help users to develop and identify improved models by comparing multiple alternative models for various products within various markets.

Similarly, U.S. Patent Application No. 6,138,103 to

30   Cheng et al. discloses a decision-making method for

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predicting uncertain demand. The Cheng system uses a matrix to represent potential demand scenarios and their relative probabilities of occurring, and these matrices are then used to calculate a production-planning schedule

5    based upon the most probable outcome of the uncertain demand. Cheng, like Milne, fails to teach manners for developing alternative algorithms for forecasting future demand as well as fine-tuning such demand forecasting algorithms.

10        Additionally, U.S. Patent No. 5,459,656 to Fields et al. discloses a system that measures and stores business demand data over a plurality of time intervals and projects the business demand for products in near-future time intervals using percentage-based demand curves. The

15    Fields system allows the creation of a plurality of demand curves for the items to determine near-future demand by using defined functions and variables. Business demand projections for current and near-future time intervals can then be revised in response to

20    variances in actual business demand data as it received. Fields, however, fails to produce forecasts that proactively take into account many factors that impact upon future demand including the variability of individual markets and the impact of product promotions.

25        Finally, U.S. Patent No. 6,032,125 to Ando discloses a demand forecasting system that allows users to forecast demand based upon algorithms derived from data of various time periods including recent months, similar periods in previous years, and combinations thereof. The Ando

30    patent, however, fails to take into account that data

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regarding past demand can come from various sources
within a single organization or supply chain (such as
sales data, returns, wholesale data, etc.).  Further,
Ando fails to teach systems or methods for deriving
5    various demand forecasting models and revising those
models over the passage of time.

Thus, there remains a need in the art for improved
systems and methods that can proactively develop
alternative models to predict demand across multiple
10   levels of an organization's supply chain so as to avoid
costly mismatches of demand and supply.


## SUMMARY OF THE INVENTION

In light of the drawbacks inherent in the prior art,
it is an object of the present invention to provide a
15   system and accompanying methods for accurately
forecasting future demand for many products and product
types in many markets.

Also, it is an object of the present invention to
provide a system and related methods that enables
20   organizations to produce and compare alternative models
of forecasted demand in order to constantly improve
demand-forecasting capabilities.

Concurrently, it is an object of the present
invention to provide such a system and method that
25   operates across distributed computer networks whereby
users can be located at various remote locations and the
system can publish selected forecasts for use by an
entire organization including downstream supply,
manufacturing and transportation planning systems.

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Similarly, it is an object of the present invention to provide a system and accompanying methods producing and identifying optimal demand forecasts that take into account independent causal factors, such as new

5    competitive products and price promotions, that will impact upon future demand.

Further, it is an object of preferred embodiments of the present invention to a system and related method whereby users can easily account for current demand

10    trends without having to produce an entirely new forecast.

Additionally, it is an object of preferred embodiments of the present invention to provide a system and related methods that allows users more easily to

15    produce and compare forecasts for related products, products within related markets, and for products taking into account different forecasting models.

In response to the above-described and other needs, the present invention provides a solution for identifying

20    and taking into account the many critical factors that drive demand by providing a multiple model framework that allows multiple alternative forecasting algorithms, including well known statistical algorithms such as Fourier and multiple linear regression ("MLR") algorithms

25    and proprietary algorithms useful for modeling the causal factors relating to various products and/or industries, to be associated with various data streams of demand history to product advanced forecasting models. The present invention helps users to determine the forecast

30    algorithm that best suits a given

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problem/industry/business from the available history
streams of demand data by enabling the production of
various forecasts for comparison with one another and,
eventually, with incoming data relating to actual demand.

5       By employing multiple models for a single product or
location, the present invention enables multiple-scenario
comparisons and analysis by letting users create
forecasts from multiple history streams (for example,
shipments data, point-of-sale data, customer order data,

10   return data, etc.) with various alternative forecast
algorithm theories. As will be readily appreciated by
one of ordinary skill in the art, there are various well-
known and proprietary statistical algorithm alternatives
that can be used in particular circumstances to predict

15   future demand based upon historical data. The multiple
model framework of the present invention enables users to
compare statistical algorithms paired with various
history streams (collectively referred to as "models") so
as to run various simulations and evaluate which model

20   will provide the best forecast for a particular product
in a given market. Once the user has decided upon which
model it will use, it can publish forecast information
provided by that model for use by its organization (such
as by a downstream supply planning program).

25       Preferred embodiments of the present invention use
an automatic tuning feature to assist users in
determining optimal parameter settings for a given
forecasting algorithm to produce the best possible
forecasting model. This feature significantly reduces

30   the time and resources necessary for users to produce an

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acceptable demand forecast from history streams of
demand data.

Embodiments of the present invention provide a
system and method whereby appropriate demand responses

5    can be dynamically forecasted whenever given events
occur, such as when a competitor lowers the price on a
particular product (such as for a promotion), or when the
user's company is launching new sales and marketing
campaigns. Utilizing the multiple model framework

10   according to the present invention allows the selection,
customization, and fine tuning of the appropriate
forecasting algorithm to apply to a given demand problem
by producing a plurality of forecasts, each forecast
taking into account different demand causal factors and

15   demand data history, and identifying and optimal forecast
for adoption. According to such embodiments, users can
accurately predict customers' buying plans and thereby
forecast the demand for a product or product line by
identifying and quantifying key variables that drive

20   demand from the available history streams of demand data.

Embodiments of the present invention recognize that
there are often several different areas for which
forecast information is obtained. To this end, the
multiple model framework of the present invention

25   supports collaborative and comparative forecasting. Such
collaborative and comparative forecasting can occur both
internally within a single organization as well as
externally across an extended supply chain community
consisting of many business partners. In this manner,

30   demand history data can be shared to create more accurate

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demand forecasts and adopted forecasts can be published
across an entire organization or extended supply chain
community. As will be readily appreciated by one of
ordinary skill in the art, the demand forecasting
5   capabilities of the present invention can be distributed
across an entire enterprise or alternatively can be used
regionally for specific geographic areas of an
enterprise.

The present invention also provides intelligent
10  event modeling capabilities and allows for management
overrides and forecast adjustments given newly received
data regarding changes in actual demand. As such, event
data is incorporated into forecast models on an ongoing
basis to help adjust forecast decisions on the fly and
15  refine the forecasting process for future endeavors. By
including both market planning and demand planning
capabilities, the present invention links product mix,
promotion, and price analyses with traditional demand
forecasting.
20      Preferred embodiments of the present invention are
computer networks and related methods that facilitate the
forecasting of the demand of goods within a supply chain
and associated planning functions. Preferably, in any
one of the embodiments of the present invention a front-
25  end user interface permits user to interact with one or
more databases to define a plurality of decision making
algorithms to customize those algorithms to leverage the
expertise of the user regarding the organization.
Additionally, the front-end user interface permits users
30  to review and modify demand forecasts and adopt

particular approved forecasts for publishing across the users' organization.

Embodiments of the present invention also utilize interactive graphical interfaces to help suppliers
5  understand the impact of events on demand. Visibility of demand is thereby given across the entire trading network using collaborative forecasting capabilities that allow user to monitor demand throughout the organization. By helping to ensure that the entire organization is, or
10  even group of collaborating organizations are, planning with the same forecast numbers, the present invention helps smooth demand variation across the trading network to facilitate more effective collaboration.

The present invention acts as an early-warning
15  system, predicting future customer demand, alerting of potential supply problems, and finding patterns undetected by traditional solutions. It enables a company within a supply chain to understand customers' demand drivers, to more accurately predict customers'
20  future needs, and to unify disparate planning processes through its multiple model framework and collaboration with other members of the supply chain.

Additional features and advantages of the invention are set forth in the description that follows, and in
25  part are apparent from the description, or may be learned by practice of the invention. The objectives and other advantages of the invention are realized and attained by the structure particularly pointed out in the written description and claims hereof as well as the appended
30  drawings.

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It is to be understood that both the foregoing
general description and the following detailed
description are exemplary and explanatory and are
intended to provide further explanation of the invention
5   as claimed.


BRIEF DESCRIPTION OF THE DRAWINGS
The accompanying drawings, which are included to
provide further understanding of the invention and are
incorporated in and constitute a part of this
specification, illustrate embodiments of the invention
10   and together with the description serve to explain the
principles of the invention.  In the drawings with like
reference numbers representing corresponding parts
throughout:
figure 1 is a schematic diagram depicting how demand
15   forecasts can be organized by demand forecasting units
according to the present invention;
figure 2 is a schematic diagram depicting how
alternative forecasting algorithms and various history
streams of demand data can be combined according to
20   embodiments of the present invention to create a multiple
model framework;
figure 3 is a combination schematic and flow diagram
depicting how the logic whereby the demand forecasting
system, of the present invention creates a forecast for a
25   given demand forecasting unit from a history stream and
user inputted causal factors according to embodiments of
the present invention;


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figures 4A, 4B, 4C and 4D are two-dimensional plots depicting the difference between forecasts that progressively take into account level, trend, seasonal effects, and casual factors;

5    figure 5 is a flow diagram depicting the manner by which the various coefficients for a forecasting algorithm are generated according to preferred embodiments of the present invention;

figure 6 is a flow diagram depicting the overall
10   process steps performed to produce a demand forecast including preparing for and performing a demand planning cycle according to embodiments of the present invention; and

figure 7 is a flow diagram depicting a process for
15   producing a forecast for each of a plurality of demand forecasting units according to preferred embodiments of the present invention;

figure 8 is a schematic diagram depicting the operational aspects and interactions of an electronic
20   demand forecasting system according to preferred embodiments of the present invention.

## DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS

Reference is now made in detail to the preferred embodiment of the present invention, examples of which
25   are illustrated in the accompanying drawings.

Generally for a given seller organization that operates as a seller or supplier, demand forecasting must be performed on a recurring basis for each item in each market. Since the demand for an item varies according to

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the market and time frame in which it is selling, demand
forecasts according to the present invention are
identified according to its demand forecasting unit
("DFU"). As depicted in figure 1, a DFU 100 according to
5    the present invention is a mechanism for categorizing
each demand forecast according to four primary types of
information. Each DFU 100 categorizes a forecast
according to one of a plurality of a demand units 101,
one of a plurality of demand groups 102, one of a
10   plurality of locations 103, and one of a plurality of
models 104. A demand unit is a unique product identifier
code that functions in a manner similar to an item number
or catalog number (i.e., it identifies the particular
product to which that DFU's forecast will apply). Demand
15   groups are categories into which demand units fall and
which are used for forecasting purposes. A demand group,
for example, might be a key account, a brand, a customer
grouping or demographic, a vendor type, or a market zone.
Therefore, each DFU contains a demand unit and a demand
20   group into which the demand unit is further classified
with other related demand units. Additionally, for each
DFU a location is specified which represents the
geographic region to which a particular forecast will
apply. Typically, the DFU location is specified at the
25   market level and does not take distribution centers into
consideration for a particular forecast. Finally, the
model specified for each DFU defines the combination of
history stream and forecast algorithm that will be used
to create forecast for that particular DFU. This history
30   stream and forecast algorithm combination, as will be

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understood further after reading the discussion of
figure 2 below, defines the statistical model that a
particular user selects to create demand forecasts.

The use of DFUs to categorize and organize forecasts
5       according to preferred embodiments of the present
invention allows users to correlate and associate related
forecasts for a particular product (demand unit), for
particular products within a given product category
(demand group), for like products being sold to a
10      particular type of customer (demand group), for a product
or like products within a given market (location), or for
a particular product within a particular market wherein .
different a forecast algorithm and history stream
combination (model) is employed.  As shown in figure 1, a
15      given DFU in the field 100' of DFUs defined by the user,
for example, may have a demand unit $DU_1$ of "080-16" (a
product number), a demand group $DG_1$ of "retail stores" (a
channel), a location $L_1$ of "South West U.S." (a market
region), and a model $M_1$ of "point-of-sale/proprietary" (a
20      demand history/algorithm combination).  A second DFU
could also be comprised of $DU_1$, $DG_1$ and $L_1$ but instead
have a model $M_2$ of "point-of-sale/Fourier" and therefore
would produce different statistical forecasts.  Such DFUs
that differ only with respect to model (either by
25      history, algorithm, or both) are referred to herein as
"model variants."

Referring now to figure 2, there is depicted a
schematic diagram that demonstrates how, for a given
demand unit, alternative forecasting algorithms 201 and
30      various history streams 202 of demand data can be

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combined by user defined DFU parameters 200 according to
the present invention to create a plurality of models
104. As will be readily appreciated by one skilled in
the art, the ability to make various combinations of
5    available history streams of demand data and forecasting
algorithms as depicted in figure 2, in conjunction with
the ability to recognize and associate model variants,
according to embodiments of the present invention
facilitates the comparison of alternative demand
10   forecasts that take into account different demand
drivers, product life cycle projections, and the like.
The ability to identify a preferred model for making
demand forecasts is thus made easier.

Similar to model variants, DFUs that differ only
15   with respect to locations are referred to herein as
"location variants." As will be readily appreciated by
one skilled in the art, demand at different locations can
often be sufficiently parallel (such as for established
products in separate and distant, yet similar, cities)
20   such that the accuracy of a forecast for one DFU can be
assessed by comparing the forecast with existing
forecasts for its location variants.

Thus, due to the multiple model framework ("MMF")
employed by the present invention, DFU model variants can
25   have multiple types of history and multiple forecast
algorithms combined to form several alternative models
for a given product. In this manner, forecasts for DFUs
which are model variants of one another can thereby be
created for comparison and eventual adoption of the best
30   model as described below.

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Additionally, a judgement forecast (as defined and
described below) for a first demand unit can be made
taking into account the statistical forecast created for
a second demand unit in the same demand group (i.e., such

5    as in the case of similar products within the same
product category). This aspect of the invention is
especially useful in situations whereby a first product
does not have a significant amount of demand history data
and is similar enough that the user can expect the second

10   product to have behave in a manner similar to how the
first product is forecasted to behave.

The present invention recognizes that there are
often several different areas from which forecast
information is obtained. To this end, the multiple model

15   framework ("MMF") the present invention can be employed
to support collaborative and comparative forecasting.
Such collaborative and comparative forecasting as
described herein can occur both internally within a
single organization as well as externally across an

20   extended supply chain community consisting of many
business partners. By employing MMF functionality, the
present invention enables multiple-scenario comparisons
and analysis by letting users create forecasts from
multiple history streams (for example, shipments data,

25   point-of-sale data, customer order data, return data,
etc., originating from various sources) using various
alternative forecast algorithm theories.

As will be readily appreciated by one of ordinary
skill in the art, there are various well known and

30   proprietary statistical algorithms that can be used

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alternatively in particular circumstances to predict
future demand based upon historical data.  The MMF of the
present invention enables users to compare statistical
algorithms paired with various history streams

5       (collectively referred to as "models") so as to run
various simulations and evaluate which model will provide
the best forecast for a particular product in a given
market.  Once the user has decided upon which model it
will use, it can publish forecast information provided by

10      that model for use by its organization (such as, for
example, by a downstream supply-planning program or
shipping managers).

In preferred embodiments of the present invention,
by employing the MMF organizations can import forecast

15      values from various external groups or other parts of
their organizations such as, for example, already
completed sales or marketing estimates, to compare to
with forecasts produced by statistical models is systems
of the present invention.  In this manner, statistical

20      forecasts produced by a system or method of the present
invention can be compared with external judgement
forecasts to help users refine models and make forecast
publication decisions accordingly.

To generate a particular forecast, the present

25      invention provides organizations with the ability to
calculate a variety of forecasts according to alternative
models and then select the results of a particular
forecast model that they feel is most accurate and would
like to submit (or "publish") for subsequent supply

30      planning.  Algorithms as utilized in the MMF are composed

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of a series of mathematical calculations that are
executed based upon history stream data in order to
create a statistical forecast. Preferred embodiments of
the present invention enable users to achieve a balance

5   between strictly statistical forecasts and judgement
forecasts by controlling the use of history data.
Statistical forecasts assume that products generate
stable demand. As such, statistical forecasts are
typically more useful to reflect the characteristics of

10   mature products that are produced and maintain long life
cycles with many customers. These forecasts rely upon a
base history (i.e., history not containing such anomalous
or unusual data points) for predictable and repeatable
demand.

15       On the other hand, judgement forecasts focus
strongly on human estimates of unstable demand. Such
forecasts are most useful with new products that are
highly promoted, those products that have few customers,
those that are fairly new, and/or those that have a short

20   life cycle. Judgement forecasts are used for special
events and non-repeatable occurrences and typically rely
upon non-base history streams.

      Referring to figure 3, there is depicted how a
forecast 308 is created for a given DFU from appropriate

25   demand data present in various history streams 303 and
inputted future causal factor information 306 according
to the demand forecasting systems and methods of the
present invention. Initially, various demand data
history streams are stored in a database like the history

30   database 301a depicted in figure 3. Obviously, the

functions for databases 301a-301c in figure 3
alternatively can performed by a single database, but,
however, separate databases are depicted in figure 3 to
more clearly depict the flows of data.  Using DFU data
5    304 (demand unit, demand group, location and model)
retrieved from a DFU database, a database server 302a
retrieves history streams 303 that contain demand data
relevant to the DFU from the history database 301a.  This
DFU and appropriate demand data history streams relevant
10   to the DFU are passed 305 to a forecast generation server
302b (like databases 301a-301c, servers 302a-302b
alternatively can be combined into a single server).
Forecast generation server 302b uses the forecast and DFU
data 305 and causal factor inputs 306 from a user (such
15   as through an input device like personal computer 308) to
produce a demand forecast 307 for the DFU.  This demand
forecast is sent to the database server 302a where it is
then stored in a forecast database 301c.  Plot 307'
provides a graphical example regarding how the demand
20   forecast 307 could appear to a user.

       When choosing the appropriate statistical algorithm
to associate with a particular DFU history stream (i.e.,
combine them to create a model) according to the present
invention, the appropriate algorithm should preferably be
25   chosen based upon the characteristics of the underlying
product.  For example, Table 1 below illustrates how a
particular product's life cycle or characteristics can
have a strong influence upon its demand patterns.

| Product Type | Phase in Life Cycle | Characteristic Sales Pattern |
|---|---|---|
| Halloween Candy | Mature Product | Predictable Seasonal Peaks |
| Spare Parts For New Automobiles | Newly Introduced Product | Sporadic Demand |
| Computer Processor Chips | Growth or Decline | Fast growth followed by sharp decline |
| Snow Shovels | Mature Product | Irregular Seasonal Peaks |

**Table 1**

According to preferred embodiments of the present

5    invention, the demand planning system supports a
combination of both well-known traditional algorithms and
proprietary algorithms.

Figures 4A, 4B, 4C and 4D are two-dimensional plots
400a-400d depicting the difference between forecasts

10   401a-401d that progressively take into account level,
trend, seasonal effects, and casual factors.  As shown in
figure 4A, the demand forecast 401a depicted represents a
forecast that predicts only the future level of demand.
In essence, forecast 401a is solely an average of past

15   demand history data and does not take into account trends
in demand, seasonal effects and causal factors.  Under
normal circumstances, the only time such a forecast would
be useful is if past demand is "lumpy" or random such
that no pattern can be deduced.  Forecast 401a by far

20   represents the most simplistic type of demand forecast
that can be produced from demand history data.  More
complex statistical forecasts also take into account the

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trend of demand, as the forecast 401b presented in
figure 4B demonstrates. While forecast 401b is a linear
forecast that takes into account demand trend (in the
case illustrated, a linear tendency for demand to
5    increase at a given rate), it will be readily appreciated
by one of ordinary skill in the art that forecasts which
utilize the trend concept can be of other forms including
quadratic and logarithmic. Additionally, even further
advanced demand forecasting algorithms take into account
10   seasonal effects. Such seasonal forecasts, such as
forecast 401c of figure 4C, predict peaks and valleys in
demand to help model past recurring periods of high and
low demand into the future. The seasonal effects that
can lead to such high and low periods of demand typically
15   vary from market to market and product to product.
Finally, the plot of figure 4D demonstrates the effect a
causal factor (such as sale price discounting) can have
on a forecast otherwise based solely upon level, trend
and seasonal effects such as forecast 401c of figure 4C.
20   For example, conventional economic theory dictates that
one would expect that demand for a given product would
increase with a decrease in price (all other things being
equal). Other causal factors besides price changes would
likewise have similar impacts upon expected demand. The
25   quantification of the effect of causal factors into
forecasting algorithms to more accurately predict the
future demand for a product is thus attempted in many of
the more sophisticated forecasting algorithms. The
ability of the present invention to provide alternative
30   forecasting models created using various forecasting

algorithms in essence advantageously allows users to use
their business judgement and experience to take into
account level, trend, seasonal effects and causal factors
identified from past demand data to various extents to
5    achieve the most accurate forecast possible given the
demand history data available.

The task of creating and maintaining a statistical
model to be associated with a particular DFU must take
into account two basic elements in order to provide
10    realistic statistical forecasts; it must take into
account historical data to generate the statistical
algorithm, and must project historical demand patterns
into the future.  Many statistical algorithms are based
on Fourier series (due to the cyclical nature of the
15    Fourier series) and contain customized sets of
coefficients (determined from past historical data) that
are intended to project demand for a given product into
the future.  Additionally, multiple linear regression
("MLR") is also used in statistical algorithms to
20    calculate forecasts for products that have multiple
external factors (causal factors) such as price, weather,
or demographics which influence the selling patterns
(i.e., demand) of products.

By way of example, it is known in the art of
25    statistical demand forecasting to utilize Fourier series
to model the demand cycle of stable products that have
either constant demand or demand that changes at a
predictable constant and/or periodic rate.  Fourier
series operate by fitting sine and cosine waves with
30    increasing frequencies and phase angles into a time

series. The first coefficient in a Fourier series when
used for demand planning represents the overall level (or
mean) of demand (a forecast 401a taking into account mean
only is depicted in figure 4A). The second coefficient

5   represents trend (or slope) which models the number of
units by which the level is changing (increasing or
decreasing) within each time period·(a forecast 401b
taking into account mean and trend is depicted in figure
4B). The remaining Fourier coefficients (present in

10  pairs) represent seasonal patterns (peaks and valleys) in
the demand history (a forecast 401c· taking into account
mean, trend and seasonal effects is depicted in figure
4C). Understandably, predictable seasonal patterns in
demand history can be very accurately modeled by sine and

15  cosine waves. Thus, Fourier type demand planning
algorithms typically produce the best results when 2 to 3
years of demand history are used to·generate the model
coefficients (although the·algorithm, of course, can
create a forecast based upon only a·few history points)

20  for a product type in point of its life cycle that
demonstrates large seasonal effects upon demand. Thus,
demand forecasting algorithms based upon Fourier series
in essence allow companies to produce forecasts that take
into account seasonal effects.

25      Additionally, statistical forecasting algorithms
derived from MLR of demand causal factors are also used
in industry. MLR extends the Fourier approach by
integrating one or more causal factors (that is, external
demand driving independent variables like price, weather,

30  demographics, and other known economic indicators) into a

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trend or cyclical forecast to help predict the influence
of such causal factors upon the selling patterns of
particular products.   MLR-based algorithms can be best
applied when there are multiple known external factors
5    that have a significant impact upon.sales or demand.
Often times, product price. and advertising efforts are
particularly strong causal factors. . Thus, MLR utilizes
level, trend, and seasonal effect predictors like the
Fourier approach but also integrates independent variable
10    causal factors and event data into the forecast.   As
evidenced by a comparison of forecasts 401c and 401d in
figures 4C and 4D, causal factors have an additive
(positive or negative) effect on the·Fourier base demand
(given by the mean, trend and seasonal effects).

15        Figure 5 is a flow diagram depicting the process 500
by which the various coefficients for a forecasting
algorithm are generated according to preferred
embodiments of the present. invention.   As shown, first
the appropriate history data is identified at step 501
20    (such as by the model definition for the particular DFU
in question).   At this point, the system identifies a
maximum number of terms (model coefficients) to attempt
to solve for at step 503.   This maximum number of terms
could be a system-set default value (for example, to
25    place an upper limit on the amount of calculating
capacity used) or a guess by the user based upon the
amount of seasonal peaks or causal factors he or she
believes have been observed in the demand history data.
Experience has shown that according to preferred
30    embodiments of the present invention that optimal

performance of process 500 will typically be achieved if
the maximum number of terms for a weekly forecast is set
at less than or equal to 12 and for a monthly forecast is
set at less than or equal to 52.

5      · Once the maximum number of terms and the history
data is selected, a least squares regression is performed
on the history as is known in the art of statistical
analysis at step 503.  At step 503, the process 500
attempts to find the coefficients of the forecasting

10    algorithm in question that produces a minimum squared
error.  In essence, step 503 of process 500 will attempt
to fit the best model forecast to the data using the
maximum number of terms allowed.    ·

       At this point, an initial forecasting model is

15    produced.  At step 504, process 500 performs a
significant amplitude test to determine how many seasonal
effect terms (an amount less than or equal to the maximum
amount of terms set at step 502) should be included in
the final model.  Starting with the peak or valley (i.e.,

20    sine wave) with the smallest amplitude, step 504
progressively eliminates the smallest peak or valley
coefficient until it finds the smallest amplitude peak or
valley that still meets an amplitude significance test
(such as exceeding a minimum percentage effect on base,

25    i.e., level and trend, demand or by exceeding a threshold
related to a value reflecting the amount of error in the
model).  As soon as the first peak or valley that has
significant amplitude is found, the system stops checking
and concludes that the remaining peak and valley

30    coefficients represent the right amount of seasonal

effects for the model. Thus, the value of the significant amplitude test factor can make it more or less likely for the process 500 to include many seasonal waves in the final forecasting model.

5      At step 505, a second least squares regression is performed on the history data selected at step 501. In this regression, however, the process 500 assumes the appropriate amount of seasonal effect terms is represented by the amount of peaks and valleys found to

10     have significant amplitude at step 504. The least squares regression of step 505 thereby produces a final forecasting model.

As will be readily appreciated by one of ordinary skill in the art, a user can calculate a demand forecast

15     employing an MLR algorithm by including only those variables that have a significant impact upon demand or alternatively by employing many causal factors. In either case, MLR-based algorithms automatically calculate the effect of each individual causal factor on sales

20     (such as by calculating the T-statistics and associated P-values for each of the coefficients). In calculating these effects, the MLR model uses future causal factors data such as, for example, a proposed change in price.

Further, proprietary demand planning and forecasting

25     algorithms are available that assume that business is not constant. Such proprietary algorithms are useful to model products with sporadic demand short life cycles, such as, for example, computer hardware. The present invention is adapted to utilize one or more of such

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proprietary models that have been or will be developed
to forecast such sporadic product life cycles.

By way of example, according to the Fourier and MLR
algorithms employed in embodiments of the present
5   invention, the forecasting models derived therefrom can
be generically described according to the equation

$$F = DM + S + CF + JF \qquad\qquad (Eq.\ 1)$$

10  wherein the 'F' is the forecast, 'DM' is the dynamic mean
which comprises the level and trend portions of the
forecast, 'S' is the total of the seasonal effect
portion, 'CF' is the total of the causal factor portion,
and 'JF' comprises the total of the judgment forecast
15  portion.  Typically, the DM and S portions of the
forecast F would be automatically derived according to a
Fourier-based approach to modeling while the CF portion
would be automatically derived according to an MLR
approach.  The JF portion is manually entered by the
20  user.  For example, a user could expect that recent
positive press write-ups would provide a positive effect
on future demand in the near term and thus could manually
introduce a positive JF portion to a given forecast to
account therefor.  Alternatively, of course, each portion
25  may be manually specified by the user.  The forecast F
for a model thereby is the summation of the dynamic mean
DM with the seasonal effects portion S (if any), with the
causal factor portion CF (if any), and with the judgment
forecast JF portion (if any).

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For the Fourier (i.e., seasonal) derived components
of a forecast model, the S portion may be comprised of
one or more seasonal effects (i.e, expected recurring
peaks and valleys in demand). The statistical regression

5   as described above, using the appropriately segmented
history data streams, calculates a series of seasonal
effect coefficients of automatically such that for time
index 't' according to the equation:

10

$$S_t = sa_1*\cos(\omega p_t) + sa_2*\sin(\omega p_t) +$$
$$sa_3*\cos(2\omega p_t) + sa_4*\sin(2\omega p_t) + \ldots$$

(Eq. 2)

where 'sa$_i$' is the seasonal amplitude coefficient
15  calculated for the particular sine or cosine wave
(amplitude being the measure of the magnitude of a
seasonal pattern), '$\omega$' is the fundamental frequency equal
to $2\pi/P$ where 'P' is the number of periods taken into
account, and 'p$_t$' is the period index.  Due to the
20  periodic nature of Fourier modeling, sine and cosine
elements will always appear in pairs such that the total
number of amplitude coefficients calculated by
statistical regression must be an even number.

For the MLR algorithm derived components of a
25  forecast model, the CF portion may be comprised of one or
more causal factor variables ("CVs") while related to,
for example, price, weather and demographics. The
statistical regression techniques as described above,
using the appropriately segmented history data streams,

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calculates one or more causal factor variable
coefficients automatically such that

$$CF = CV_1 * CVC_1 + CV_2 * CVC_2 + \ldots \qquad (Eq.\ 3)$$

5

where '$CVC_i$' is the causal factor coefficient calculated
for causal factor variable '$CV_i$.'

Mathematically, to generate an MLR-based model, the
present invention solves the following linear model for
10   each causal factor identified by the user:

$$H = \beta_0 + CVC_1 X_1 + \varepsilon \qquad (Eq.\ 4)$$

where 'H' is the history containing non-base evidence of
15   the causal factors impact upon demand, $\beta_0$ is the level
(intercept) to be calculated by the system from the
history, $X_1$ is the causal factor value inputs evidenced
in the history input by the user, $CVC_1$ (the coefficient
as defined above) is calculated by the system from the
20   history representing the proportional effect of a given
causal factor value, and $\varepsilon$ is the system calculated
measure of error. Necessarily, in performing the
statistical regression, it is desired to calculate values
for $CVC_i$ and $\beta_0$ that minimize the value of $\varepsilon$. Once $CVC_i$
25   is calculated for each causal factor variable $CV_i$, then
Equation 3 can be utilized to calculate the CF for user-
defined future values of $CV_i$.

As will be readily appreciated by one of ordinary
skill in the art, once causal factors for the demand of a

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particular DFU have been identified, the historical and
anticipated future values (for example, a planned price
discount for a particular demand unit) of those causal
factors must be inputted by a user and stored in the
5    system, such as in a database for use by the demand
forecasting system in creating a forecast with a model
that uses causal factors.

Once a MLR forecast has been generated and the
forecast has been compared with actual demand the present
10   invention enables users to fine-tune to coefficients of
the MLR forecasting algorithms. For current history
points that are anomalies (excessively high or low and
will not be repeated in the future), demand planners can
mask specific history points that are to be excluded from
15   the model.

In preferred embodiments of the present invention,
users can be prompted to create causal factor types when
establishing history streams for DFUs that are going to
use MLR algorithms for modeling. A causal factor type
20   usually represents a category or grouping of causal
factors in order to aggregate data points. For example,
holidays or price changes can serve as causal factor
types. Once causal factor types have been created, the
user can be prompted to define individual causal factors
25   that may be present within the history streams. For
example, all holidays used as causal factors can share
the same causal factor type of "holiday". However, two
separate holidays, such as Christmas and Easter, will
have individual history streams that are related to the

historical demand changes that occur whenever the causal factor occurs.

For any causal factors that are included in a forecast algorithm calculation, the coefficient values

5    and statistical values (such as T-statistics) will be stored and associated with the causal factor history. As is known in the art of statistical analysis, the T-statistic is used to measure the significance of an individual variable upon the result of a multivariable

10   function. Generally speaking, a variable (causal factor) has a significant impact upon the value of the function (forecasted demand) if the T-statistic is equal to or greater than two, or equal to or less than negative two.

Referring to figure 6, it is shown that the demand

15   planning process 600 according to preferred embodiments of the present invention includes five basic procedures. Typically, a user would perform these five procedures on a recurring basis whenever a new set of demand forecasts is desired or necessary. As shown in figure 6, at step

20   601, the user sets up the demand forecasting environment by identifying and arranging demand history data stream feeds from various internal and external sources, defining DFUs by associating demand units and demand groups with locations and models, and initializing

25   various databases (such as history, DFU, and forecast databases) for storing relevant information entered into and produced by the demand planning system. In this first step, the user also selects particular DFUs for which he or she desires to create forecasts.

30   Understandably, the number of DFUs selected at step 601

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can range from a single DFU, through a group of DFUs
(such as those having identical demand groups or being
model or location variants) up to and including all
currently defined DFUs.

5       Whenever products are added to or removed from the
user's organization's offerings, the corresponding DFU
information must be added, edited or removed from the DFU
database.  Thus, also at step 601, DFUs and their
constituent parts are continuously updated, modified or

10    deleted to reflect such product changes.  Such changes to
the DFUs are stored in the appropriate databases such
that they then are reflected in subsequent runs of the
demand planning process 600.

        As shown by the figure, step 602 immediately follows

15    step 601 and entails preparing a forecast for each DFU
selected in step 601.  Step 602 essentially comprises the
performance of a set of procedures for generating a
demand forecast; this set of procedures comprises a
forecast generation cycle that will be disclosed in more

20    detail by the discussion of figure 7 and its steps 701-
707 below.  The completion of step 602 provides the user
and the demand forecasting systems according to the
present invention with a separate demand forecast for
each DFU selected at step 601.

25       Referring now to figure 7, there is presented a flow
diagram that depicts step 602 in more detail.  As shown
by figure 7, steps 701-707 are repeated for each "active"
DFU (i.e., DFUs that are having new forecasts created by
process 600).  Each cycle of steps 701-707, a user

30    prepares and maintains history data at step 701.  Demand

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history data stored according to the present invention
at step 701 includes, for example, streams of shipment,
order, and/or point-of-sale demand data for each DFU as
well as related information including past promotions,

5    price changes and unusual events.  The demand planning
system according to the present invention stores such
demand history data in a history database.  Generally,
demand history data can be broken into two types: base
and non-base.  Base history is demand data that is

10   predictable and repeatable.  Conversely, non-base history
is that part of demand that is due to special events,
such as promotions or extreme market circumstances.  As
such, non-base history is generally comprised of that
portion of impacts upon past demand that are not

15   anticipated to repeat themselves from one year to the
next or otherwise in a periodic manner.  However, non-
base history is still stored within the history database
to help users forecast the impact of special events upon
future demand (as well as to identify and model the

20   impacts of causal factors as described above with respect
to figures 3 and 5).  The demand forecasting process 600
uses only base history to develop and fine-tune the
level, trend and seasonal aspects of a particular model.
Non-base history is only used on a case by case basis to

25   help predict the impact upon demand that will be caused
by contemplated or anticipated special events in the form
of causal factors.  At step 701, the base and non-base
history data is appropriately segregated.

As will be readily appreciated by one of ordinary

30   skill in the art, demand history data often includes data

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points (such as spikes or valleys in demand) that can
cause problems if they are included within calculations
to predict future demand.  Examples of such problematic
data include variation in demand caused by unusual market
5    conditions, decreases in demand due to obsolete or
superseded products, general data errors, and the
inability of the user to distinguish between base and
non-base data.  In order to account for such problematic
data in base or non-base history, at step 701, the user
10   is provided the opportunity to adjust history to overcome
such problems.  Mechanisms by which a user can adjust
history data include manually editing extremely high or
low values, controlling the time period of the relative
history used to ignore periods of sporadic and/or
15   otherwise unreliable history, and masking specific
periods of unreliable and/or sporadic history.

Once the relevant histories have been prepared and
maintained at step 701, demand forecasting systems that
utilize process 600 according to the present invention
20   generate forecasts at step 702 (as described in detail by
figure 3) using the particular statistical forecasting
algorithm associated with that history by the active DFU.
To generate a new model for demand forecasting, a user at
step 103 attempts to determine relevant coefficients for
25   the particular demand forecasting algorithm derived from
the pattern of past demand as evidenced by the
appropriate history.  The determination of such
coefficients is performed using known and accepted
statistical regression methodologies as described above

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with respect to figures 3 and 5. At this point, an
initial forecast is provided for review by the user.

In some preferred embodiments of the present
invention, when models are created at step 702 the

5    process 600 utilizes an automatic tuner when generating
the model from the associated algorithm and demand
history data. The automatic tuner is an iterative
algorithm that, when activated by the user, identifies
forecast model error helps to improve the quality of

10   future demand forecasts. The automatic tuner performs an
evaluation of the model prepared in step 702 (before
passing to step 703) that attempts to identify an optimal
model based upon two factors; model fit (the amount of
error between the forecasted demand and the actual

15   demand) and feasibility. The model's coefficients that
have the best model fit but that still also satisfy the
feasibility analysis is considered the optimal model
according to the present invention. When determining
error, the present invention can utilize any known and

20   accepted statistical measurement of error including mean
absolute deviation, mean squared error, smoothed mean
squared error, root mean squared error, and root mean
absolute deviation. In determining whether changes to a
forecast algorithm coefficient proposed by the auto-tuner

25   is feasible, present invention utilizes a fuzzy logic
that evaluates and balances indicators of the following
five attributes: smoothness of the dynamic mean,
stability of the seasonal profile, distribution of
positive and negative errors, forecast explosion, and

30   continuity of the fitted forecast error during the most

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recent periods. By way of example, demand more often than not tends to be smooth rather than volatile. Thus, the auto-tuner attempts to prevent causal factors from making forecasted demand overly reactive. Additionally,

5 by way of further example, more often than not demand does not experience extreme increases or decreases (explosions). In this manner, the fuzzy logic compares how changes in causal factors effects the five fuzzy logic factors as a whole. The automatic tuner thereby

10 reviews the model generated by the statistical regressions and makes certain that the model produced is feasible on top of providing a good fit with the history data.

After an initial forecast has been produced at step

15 702, the demand forecasting process 600 of the present invention at step 703 enables users to leverage their knowledge of their organization in order to fine-tune their particular model. While fine-tuning, users can introduce and/or discontinue products, limit history to a

20 particular time period, adjust individual parameters where coefficients manually, mask certain history points or periods, or manually edit base level or trend coefficients.

For example, if a user knows that a change in the

25 demand pattern occurred at a certain point in history (i.e., following a large and successful advertising campaign), he or she might desire to develop a model based only upon demand history subsequent to that change. Additionally, the users may decide to fine-tune

30 parameters of a statistically model manually by, for

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example, instructing the system to weigh the most recent
history data with more impact in determining coefficients
of the model than older history data. Further, after
reviewing the initial forecast, the user can modify the

5    model by revising the history (in a manner similar to
that discussed above with respect to step 701) such as by
masking irregular data periods. In this manner, a "fine-
tuned" initial forecast is created and passed on to step
704.

10    At step 704, the system proceeds to adjust the
statistical forecast produced by a particular model such
that the forecast takes into account planned marketing
strategies, competitive events, judgment-based forecast
effects, or occasional one time occurrences. Such

15    unusual occurrences come in the form of both external and
internal events. An external event is a planned strategy
designed by the user or its organization to stimulate
demand. Additionally, external events can include the
introduction of a new product by a competitor, or

20    anticipated cannibalization of market by new products.
An eternal event is a business condition such as a
promotion, deal, or new product introduction.
Additionally, such unusual occurrences can also include
overrides that effect catastrophic situations

25    (hurricanes, blizzards) and shifts in the market place.
For example, if the user knew that the organization
desired to offer a promotion, such as a customer price
rebate, for the active DFU and if the forecast model
generated at step 702 had utilized relevant non-base

30    history to account for the impact of customer rebates by

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introducing an appropriate causal factor, the user would
be able to input various values for the causal factor
(i.e., $5 rebate, $10 rebate, etc.) into the demand
planning system.  The system would then allow the user to
5   view the impact that the various values of the causal
factor has upon forecasted demand (such as by side by
side graphical displays or otherwise).  Once the user has
decided upon a particular value for all the causal
factors employed in the active DFU's model step 704 is
10  complete.

      After the forecast has been adjusted to account for
such unusual occurrences at step 704, the DFU forecast is
finalized at step 705.  This finalized forecast is stored
in the forecast database and is thereby made available to
15  the user for comparison with finalized forecasts for
other DFUs at step 603 in figure 6.

      After the forecast is finalized and stored in the
database at step 705, the demand forecasting process
comes to a close for the active DFU.  At step 706, the
20  demand forecasting system of the present invention stores
historical forecast data, stores forecast performance
data, and initializes the database to store updates of
demand histories as new data streams are obtained such
that this new data can be used in future runs of process
25  600 or optionally later in the current demand forecasting
process 600 at step 605 as will be described below.

      By storing the forecast data at the end of each
demand forecasting cycle for a particular DFU, the demand
forecasting system of the present invention builds a
30  history of forecast and model data that it can then use,

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together with actual demand, to track performances of
individual models over a time period.  This forecast
performance data can be used to provide feedback to the
forecasting process and help to improve its accuracy.

5    Additionally, to maintain and evaluate demand forecasts
that are current, the system continuously updates
relevant DFU histories with actual demand data.

        As shown by figure 7, steps 701-706 are repeated for
each DFU selected in step 601 until it a finalized

10   forecast has been prepared for each and the last DFU
condition at 707 is satisfied.  Step 603 is thereby
provided with a finalized forecast for each DFU selected
at step 601.

        Referring again to figure 6, the user is presented

15   with each finalized forecast for the DFUs and is able to
review and compare the forecasts.  At this step, the user
is able to compare, for example, forecasts for model
variants, location variants, and products that fall into
the same demand groups (depending upon what DFUs were

20   selected at step 601) to select the best current forecast
for a particular product (demand unit) within a market.
These selected forecasts are then published at step 604.

        When the forecasts for the selected DFUs are
published at step 604, these demand forecasts are in

25   essence made "official" in that they then are associated
with (i.e., as opposed to an alternative model variant
DFU's forecast that was found to be less desirable at
step 603) the appropriate demand unit, demand group and
location combination across the entire organization.  In

30   this manner, published forecasts can be used by other

                                40

parts of the organization including separate departments
(such as sales and marketing) or by downstream electronic
planning systems (such as manufacturing planning, supply
chain planning, and transportation network planning

5    systems).

According to more preferred embodiments of the
present invention, adjustments can be made to a published
demand forecast at step 605 (depicted in broken lines to
emphasize the optional nature of the step) in order to

10   account for the relative popularity of a product
promotion program (rebate, drop in price, etc.) once the
program is begun by using actual demand (typically,
sales) data as it becomes available. In such
embodiments, the invention uses available actual demand

15   data to calculate a forecast adjustment factor "FAF"
which is used to modify the current published forecast
according to the equation:

$$\text{Forecast}_i = \text{Forecast}_o * \text{FAF} \qquad (Eq.\ 5)$$

20

wherein "$\text{Forecast}_i$" is the initial "pre-break" demand
forecast (i.e., the current published forecast before the
actual demand data is taken into account) and "$\text{Forecast}_o$"
is the adjusted "post-break" (i.e., after the actual

25   demand data is taken into account) demand forecast. The
FAF is calculated according to the following equation:

$$\text{FAF} \quad = \quad \frac{\text{Pre-Break Actual Demand}}{\text{Pre-Break Forecasted Demand}} \qquad (Eq.\ 6)$$

30

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where an adjusted forecast, or Day "X" Post-Break
Forecast, is calculated from the date X through the end
of the promotion program with "X" being the date on which
the adjusted forecast is calculated.  By way of example,
on the morning of the third day of a price promotion for
a given DFU an adjusted forecast is desired, the actual
demand data (in the form of retail sales) for the first
two days are depicted below in Table 2 below.

| Date | Pre-Break Forecast (# Units) | Actual Sales (# Units) |
|------|------------------------------|------------------------|
| Day 1 | 45 | 52 |
| Day 2 | 42 | 55 |

**Table 2**

Calculated according to *Equation 6* above, the forecast
adjustment factor would be:

$$(52 + 55) \; / \; (45 + 42) \; = \; 1.2299$$

thus creating a Day 3 Post-Break Forecast as depicted in
Table 3 below.

| Date | Pre-Break Forecast (# Units) | Day 3 Post-Break Forecast |
|------|------------------------------|---------------------------|
| Day 3 | 21 | 26 |
| Day 4 | 25 | 31 |
| Day 5 | 28 | 34 |
| Day 6 | 31 | 38 |
| Day 7 | 35 | 43 |

**Table 3**

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When reviewing Table 3 above, it should be noted that post-break forecast values should be rounded up to the next integer number.  In this manner, an adjusted

5   forecast is obtained and can be published by the user within its organization for use in, among other things, supply, manufacturing and transportation planning.

It will be understood by one of ordinary skill in the art that demand forecasting process 600 will require

10  different amounts and types of interaction and oversight by users depending upon the amount of "new" information being processed.  In instances wherein demand history stream data has already been segregated into base and non-base history (during previous runs of demand

15  forecasting process 600) and no new history is available, step 701 could merely entail the demand forecasting system.identifying the appropriate previously-segregated history stream in the appropriate database.  Similarly, if the user over time has developed a particularly

20  accurate and trusted model for forecasting demand for a particular DFU, then review of a finalized forecast at step 603 above would most likely.serve as a mere formality before the forecast is published at step 604. Conversely, in instances wherein a new product or DFU has

25  been defined, relatively more interaction by the user will be necessary.  However, in this manner, as records are built up in the various databases regarding previous runs of demand forecasting process 600, the work of the user in making decisions (identifying and segregating

30  histories, etc.) typically is lessened.

Referring now to figure 8, there is schematically
depicted components of an electronic demand forecasting
system 800 for creating and publishing demand forecasts
according to one embodiment of the present invention.
5  The operational aspects and interactions of individual
elements of one preferred embodiment of the electronic
demand forecasting system 800 has previously been
described above with respect to figure 3.  As shown in
figure 8, the electronic demand forecasting system 800 is
10  comprised of a plurality of computerized systems in
electronic intercommunication, including: a forecast
generation system 801, a GUI (graphical user interface)
and Web platform system 803, and a database system 802.
Each of the systems 801-803 that form the forecasting
15  system 800 are comprised of suitable servers (computing
devices), storage devices (including databases), memory
devices and support hardware as is known in the art of
computer networks to achieve the functions of each system
801-803 as hereinafter described.  It will, however, be
20  readily appreciated by one of ordinary skill in the art
that the functions of systems 801-803 can be
alternatively performed by a single computing device or
by many computing devices in electronic communication.
The three systems 801-803 that comprise electronic demand
25  forecasting system 800 are meant to merely demonstrate
how a preferred system according to the present invention
would operate in a sample working environment.

Forecast generation system 801 provides the
processing power, support electronics and logic necessary
30  to create models for DFUs from appropriate history

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streams, statistical forecasting algorithms and user
inputs according to the processes described above with
respect to figures 3, 5, 6 and 7. As shown by the
figure, forecast generation system 801 is in electronic
5    communication with the GUI and Web platform system 803 to
obtain inputs and provide outputs to the user. Further,
forecast generation system 801 and is in electronic
communication with the database system to obtain demand
history data, DFU descriptions, algorithm functions and
10   other stored data as necessary during a forecast
generation process.

     GUI and Web platform system 803 acts a front-end to
the forecasting system 800 and allows users to provide
inputs as necessary to the system as well as view and
15   compare forecasts. As is known in the art of computer
networking, a user can use a user interface device 805,
such as a workstation or personal computer, to view and
input data 805' as required by the processes described
above. Since preferred embodiments of the present
20   invention are computer networks, a front-end user
interface is necessary to permit users to interact with
one or more databases in the database system 802 and to
define a plurality of decision making algorithms. The
front-end user interface permits users to review and
25   modify demand forecasts and adopt particular approved
forecasts for publishing across the users' organization.
Preferably, the front-end user interface supports
graphical interaction and access over the distributed
networks such as the Internet. As such, the present
30   invention helps organizations understand the impact of

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events on demand.  Further, the use of a distributed
network can provide visibility of demand forecasts across
an entire collaborative organization.

Database system 802 comprises electronic data

5  storage devices to store various information used by the
forecast generation system 801 to generate demand
forecasts according to the present invention.  The
database system may comprise a plurality of relational
databases (such as a history database, DFU database, and

10  forecast database) or a single unified database table.
Information can be obtained from the databases by the GUI
and Web platform system 803 or the forecast generation
system 801 as necessary or can be obtained therefrom.

Optionally, demand forecasting system 800 can be

15  electronically interconnected to external computing
systems to provide additional flexibility and utility
(such external computing systems are shown in broken
lines in figure 8 to signify their optional nature).  For
instance, demand forecasting system 800 optionally can be

20  electronically connected to an external electronic demand
data source 804 to obtain data feeds 804' regarding up to
the minute demand data (such as sales information).  In
this manner, the maintenance of history stream data can
be simplified by taking advantage of data generated and

25  inputted by third parties (as opposed to users having to
enter it themselves).  Similarly, demand forecasting
system 800 optionally can be electronically connected to
external electronic computing and management systems
within and without the organization, including a supply

30  planning system 806, manufacturing planning system 807

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and a transportation planning system 808.
Understandably, demand forecasts published by the
forecast generation system 801 can be transmitted 800'
electronically to systems 806-808 for use in proactively

5   readying other areas of the organization for expected
demand.  For example, the published forecasts can be used
to order necessary raw materials, schedule plant
resources for manufacturing according to the expected
amount of demand, and for reserving the amount of

10  transportation services expected to be necessary to
distribute orders.

One of ordinary skill in the art will appreciate
that the demand forecasting algorithms may be modified to
take into account specific needs and/or problems

15  encountered in particular industries or situations. Thus,
the illustrative algorithms should not be construed to
limit the present invention as is claimed.

Although the present invention is preferably
implemented in software, this is not a limitation of the

20  present invention as those of ordinary skill in the art
can appreciate that the present invention can be
implemented in hardware or in various combinations of
hardware and software, without departing from the scope
of the invention.  Modifications and substitutions by

25  those of ordinary skill in the art are considered to be
within the scope of the present invention, which is not
to be limited except by the claims that follow.

The foregoing description of the preferred
embodiments of the present invention has been presented

30  for the purposes of illustration and description.  It

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will be apparent to those of ordinary skill in the art
that various modifications and variations can be made to
the disclosed embodiments and concepts of the present
invention without departing from the spirit or scope of
5   the invention as claimed.

**What is claimed is:**

1.    A method for forecasting future demand, said method comprising:

  providing a plurality of demand forecasting algorithms and a plurality of demand data history streams, said history streams pertaining to a particular product at a location;

  creating more than one model for the product at the location, each said model comprising a pairing of one of said demand forecasting algorithms and one of said demand data history streams;

  calculating a forecast for each model by statistical regression of each model's history stream using its paired model's forecasting algorithm;

  comparing said forecasts for said more than one models and identifying certain forecasts as finalized; and

  publishing said finalized forecasts.


2.    The method according to claim 1, wherein said step of calculating a forecast for each model comprises creating an initial forecast for each model such that said initial forecast has a minimum error when compared to its demand data history stream and tuning said initial forecast to make it feasible.


3.    The method according to claim 2, wherein said step of tuning said initial forecast comprises balancing a

plurality of feasibility factors selected from the
group consisting of smoothness of a dynamic mean,
stability of a seasonal profile, distribution of
positive and negative errors, forecast explosion, and
continuity of error of the initial forecast during
recent history.


4.    The method according to claim 1, wherein each
forecast is identified according to a demand forecasting
unit, and wherein said demand forecasting unit comprises
a demand unit, a demand group, a location, and a model.


5.    The method according to claim 1, further comprising
adjusting said published finalized forecasts according
to a ratio of actual demand data over demand predicted
by said forecasts.


6.    The method according to claim 5, wherein said ratio
is multiplied by a remainder of the predicted demand of
the published finalized forecast to produce an adjusted
published forecast.


7.    The method according to claim 6, wherein more than
one models created allows a user to compare model
variant forecasts, location variant forecasts, and
forecasts for similar products.


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8.    The method according to claim 6, wherein
calculating a forecast comprising identifying a
significant number of forecast terms and preparing
forecast using said significant number of forecast
terms.

9.    A system for creating forecasts of future demand,
said system comprising:
      means for providing a plurality of demand
forecasting algorithms and a plurality of demand data
history streams, said history streams pertaining to a
particular product at a location;
      means for creating more than one model for the
product at the location, each said model comprising a
pairing of one of said demand forecasting algorithms and
one of said demand data history streams;
      means for calculating a forecast for each model by
statistical regression of each model's history stream
using its paired model's forecasting algorithm;
      means for comparing said forecasts for said more
than one models and identifying certain forecasts as
finalized; and
      means for publishing said finalized forecasts.

10.  A system according to claim 9, wherein said means
for calculating a forecast is adapted to select history
data related to said history stream, and perform a
least-squares regression on said history data.

11. A method for forecasting future demand, said method comprising the steps of:

setting up a database and defining Demand Forecasting Units (DFUs), each of said DFUs pertaining to a particular product at a particular location;

preparing a forecast for each of the DFUs;

reviewing said prepared forecasts; and

for one or more of said DFUs, publishing said reviewed forecasts associated with said DFUs.

12. The method of claim 11 further comprising the steps of:

adjusting one or more of said published forecasts; and

republishing said adjusted forecasts.

13. The method of claim 11, wherein said forecast preparing step further comprises:

identifying active DFUs, and for each of said active DFUs:

preparing a history stream;

associating a demand forecasting algorithm to said history stream; and

using said history stream and said demand forecasting algorithm to generate an active DFU forecast.

14. The method of claim 13, wherein said forecast preparing step further comprises fine-tuning said history stream and said demand forecasting algorithm.

15. The method of claim 11, wherein said forecast preparing step further comprises adjusting parameters used to form said DFU forecast.

16. The method of claim 13, wherein said forecast preparing step further comprises finalizing said DFU forecasts for each of said active DFUs.

17. The method of claim 16, wherein said forecast preparing step further comprises closing a forecast period for each of said DFU forecasts.

18. The method of claim 13, wherein said step of using said history stream and said demand forecasting algorithm to generating an active DFU forecast further comprises:

    selecting history data related to said history stream, and

    performing a least-squares regression on said history data.

19. The method of claim 18, wherein said step of selecting history data related to said history stream comprises identifying a maximum number of terms in said history stream, and wherein the step of performing a least-squares regression comprises using only the maximum number of terms.

20. The method of claim 19, wherein said step of using said history stream and said demand forecasting algorithm to generating an active DFU forecast further

comprises testing of said terms for significant amplitude.

21.    The method of claim 20, wherein said step of using said history stream and said demand forecasting algorithm to generating an active DFU forecast further comprises using only said terms having significant amplitude greater than a preset minimum.
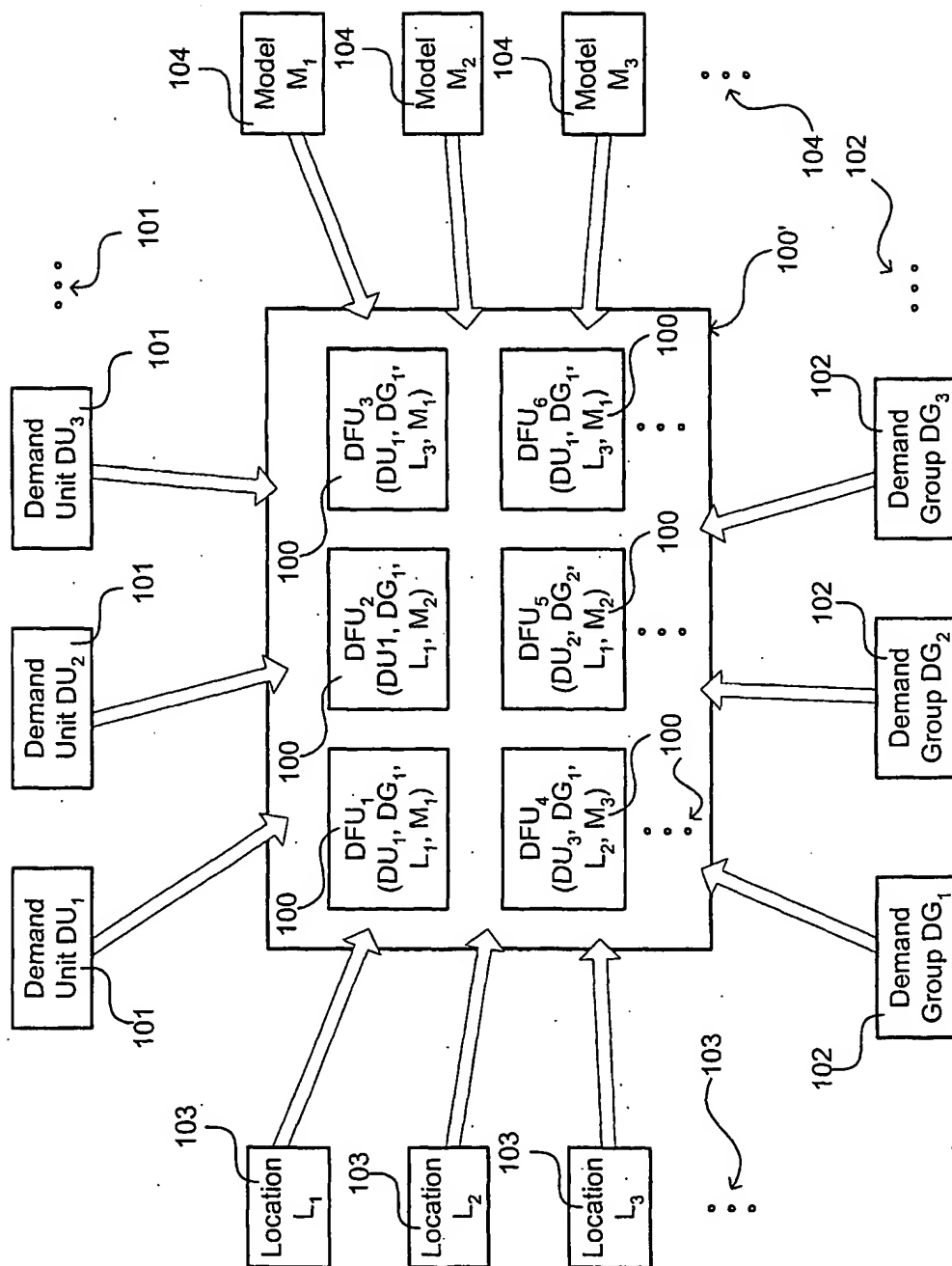
Model M$_1$ 104
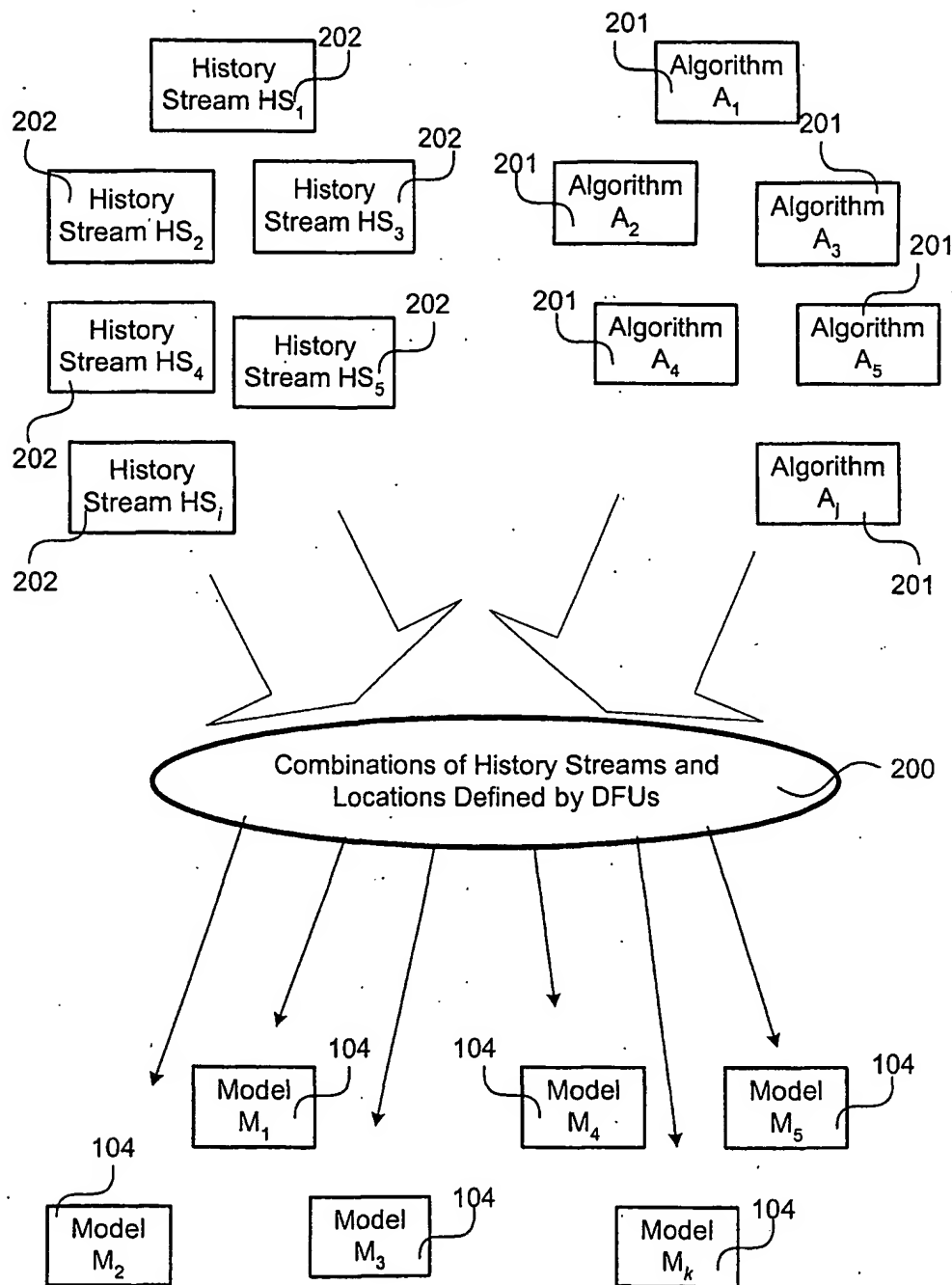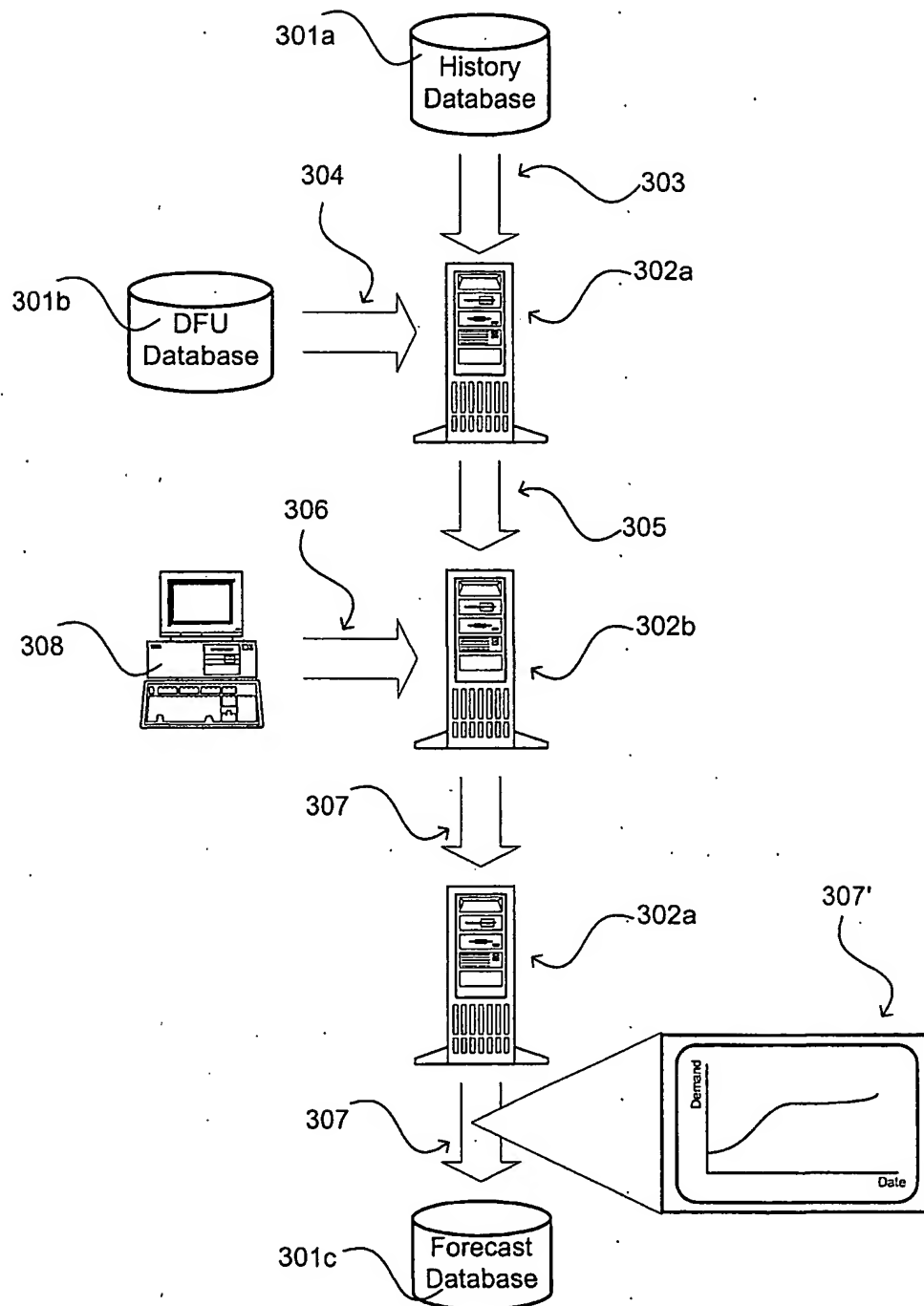
Model M$_2$ 104

Model M$_3$ 104

104

101

101

Demand Unit DU$_3$ 101

Demand Unit DU$_2$ 101

Demand Unit DU$_1$ 101

100'

102

100

100

DFU$_3$ (DU$_1$, DG$_1$, L$_3$, M$_1$)

DFU$_6$ (DU$_1$, DG$_1$, L$_3$, M$_1$)

DFU$_2$ (DU1, DG$_1$, L$_1$, M$_2$)

DFU$_5$ (DU$_2$, DG$_2$, L$_1$, M$_2$)

DFU$_1$ (DU$_1$, DG$_1$, L$_1$, M$_1$)

DFU$_4$ (DU$_3$, DG$_1$, L$_2$, M$_3$)

100

100

100

100

102

Demand Group DG$_3$ 102

Demand Group DG$_2$ 102

Demand Group DG$_1$ 102

103

103

Location L$_1$ 103

Location L$_2$ 103
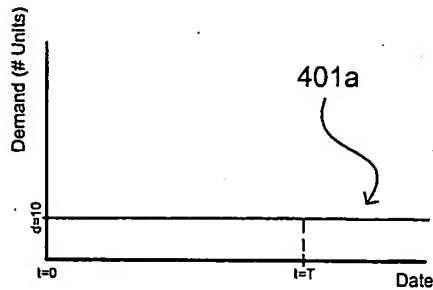
Location L$_3$ 103
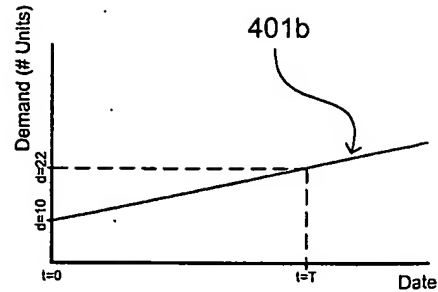
Figure 1

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Figure 2

<u>Figure 3</u>

Level = 10
Trend = 0
Seasonal Effects = (0,0)
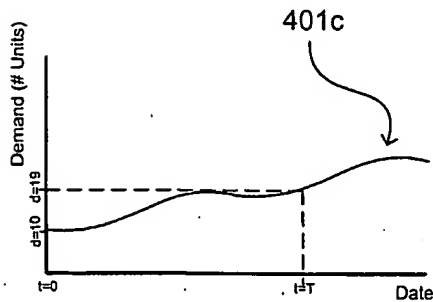Causal Effect = 0

**Forecast Demand$_{t=T}$ = 10**

## Figure 4A

Level = 10
Trend = 1.3
Seasonal Effects = (0,0)
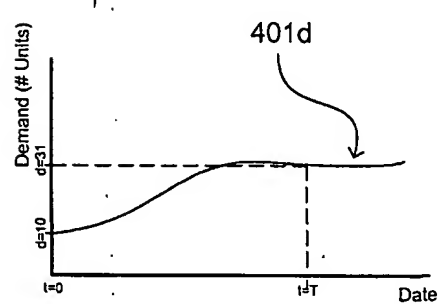Causal Effect = 0

**Forecast Demand$_{t=T}$ = 22**

## Figure 4B

Level = 10
Trend = 1.3
Seasonal Effects = (0.8,0.5)
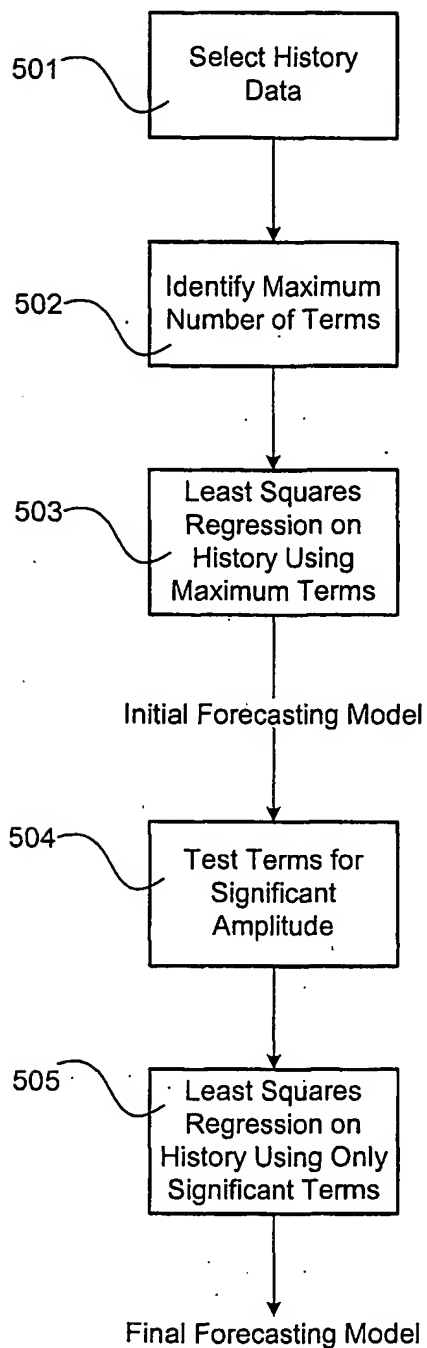Causal Effect = 0

**Forecast Demand$_{t=T}$ = 19**

## Figure 4C

Level = 10
Trend = 1.3
Seasonal Effects = (0.8,0.5)
Causal Effect = +0.63

**.Forecast Demand$_{t=T}$ = 31**

## Figure 4D

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501 — Select History Data

502 — Identify Maximum Number of Terms

503 — Least Squares Regression on History Using Maximum Terms

Initial Forecasting Model

504 — Test Terms for Significant Amplitude

505 — Least Squares Regression on History Using Only Significant Terms

Final Forecasting Model

500

<u>Figure 5</u>

601 → Setup Database and Define DFUs

602 → Prepare a Forecast for Each DFU

603 → Review Forecast Calculated for Each DFU

604 → Publish Forecasts for Selected DFUs

605 → Adjust Published Forecasts and Re-publish

600

<u>Figure 6</u>

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701 — **Identify Active DFU and Prepare its History Stream**

From Step 601, Figure 6

No

702 — **Generate Active DFU Forecast using History and Algorithm**

**Last DFU?** 707

Yes

To Step 603, Figure 6

703 — **Fine Tune Model for Active DFU**

704 — **Adjust Forecast Parameters**

**Close Forecast Period for the Active DFU** 706

705 — **Finalize Forecast for Active DFU**
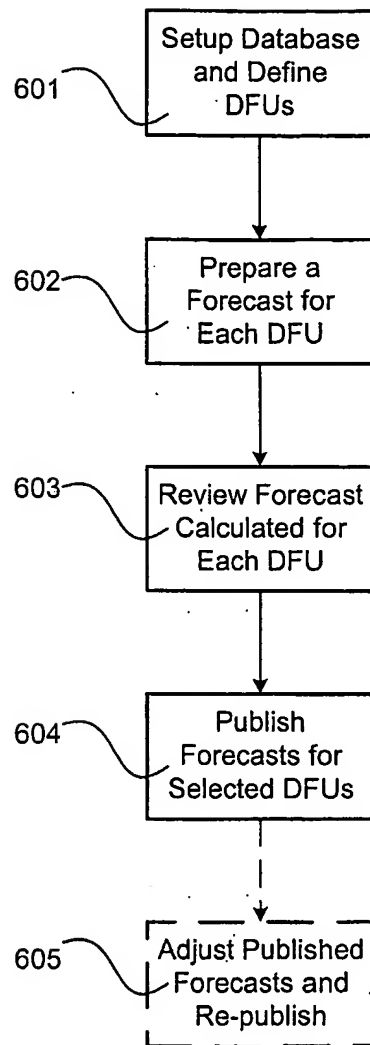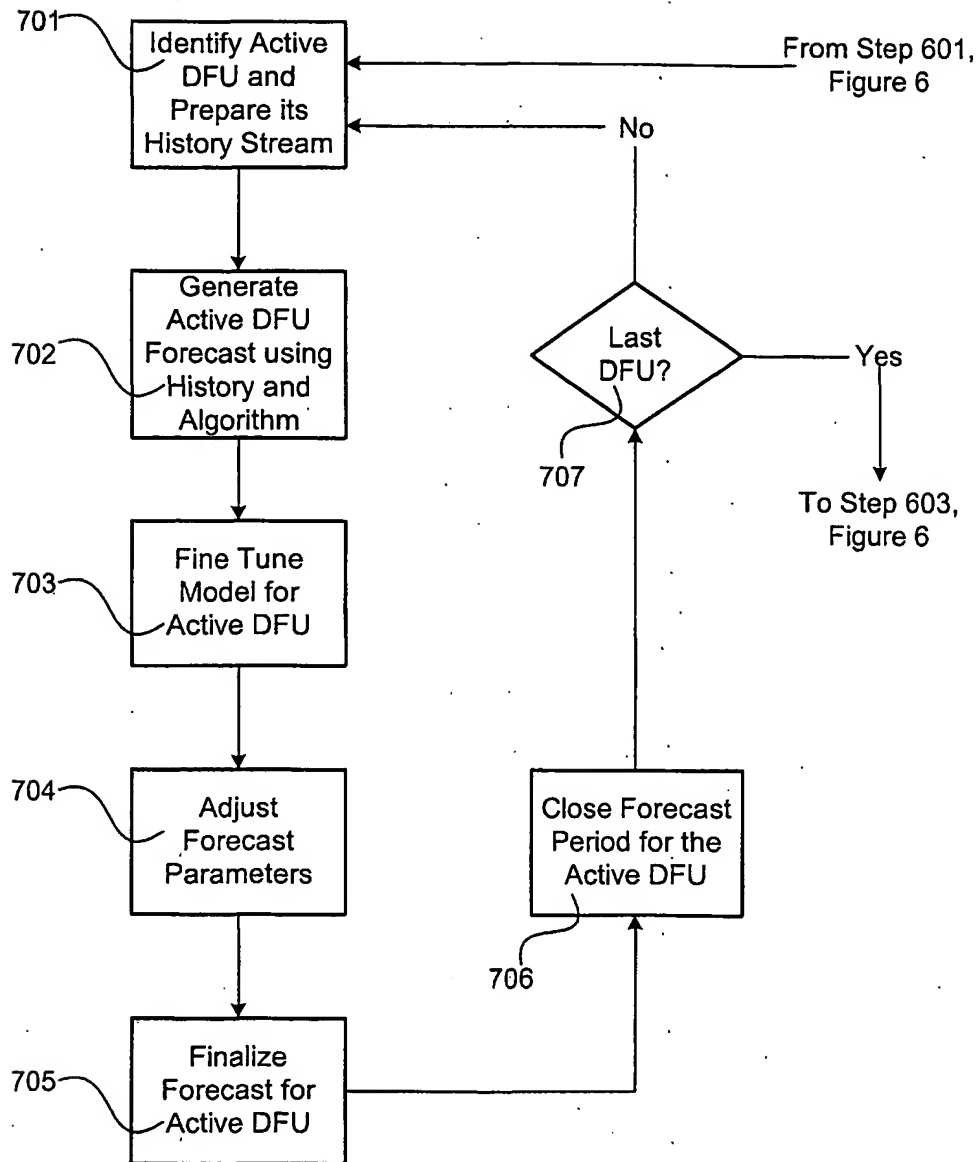
<u>Figure 7</u>

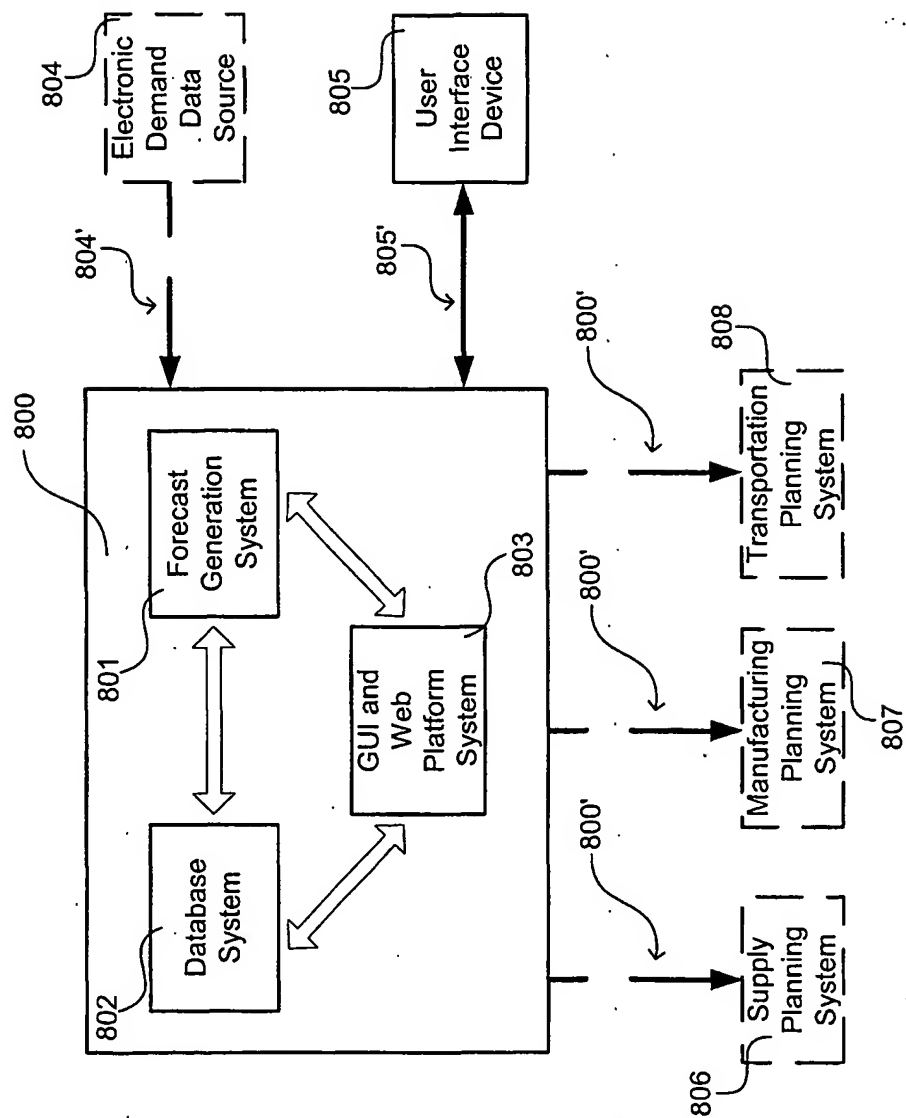<u>602</u>

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Figure 8

# INTERNATIONAL SEARCH REPORT

International application No.

PCT/US01/42824

| A. | CLASSIFICATION OF SUBJECT MATTER |
|---|---|

IPC(7)  :  G06F 17/60
US CL  :  705/10

According to International Patent Classification (IPC) or to both national classification and IPC

| B. | FIELDS SEARCHED |
|---|---|

Minimum documentation searched (classification system followed by classification symbols)
U.S. : 705/10

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)
EAST and PROQUEST terms: future, demand, forecast, algorithm

| C. | DOCUMENTS CONSIDERED TO BE RELEVANT | |
|---|---|---|
| Category * | Citation of document, with indication, where appropriate, of the relevant passages | Relevant to claim No. |
| Y | US 5,459,656 A (FIELDS et al) 17 October 1995, see entire document | 1-21 |
| Y | US 5,446,890 A (RENSLO et al) 29 August 1995, see entire document | 1-21 |
| Y | US 6,032,125 A (ANDO) 29 February 2000, see entire document | 1-21 |
| Y | US 5,712,985 A (LEE et al) 27 January 1998, see entire document | 1-21 |
| Y,P | US 6,205,431 B1 (WILLEMAIN et al) 20 March 2001, see entire document | 1-10 |
| Y | KAPLAN, A. J., Bayesian Approach To Inventory Control of New Parts, IIE Transactions, June 1988, Volume 20 Issue 2, pages 151-156 | 1-10 |

☐ Further documents are listed in the continuation of Box C.  ☐ See patent family annex.

| * | Special categories of cited documents: | "T" | later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention |
|---|---|---|---|
| "A" | document defining the general state of the art which is not considered to be of particular relevance | | |
| "E" | earlier application or patent published on or after the international filing date | "X" | document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone |
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| "O" | document referring to an oral disclosure, use, exhibition or other means | | |
| "P" | document published prior to the international filing date but later than the priority date claimed | "&" | document member of the same patent family |

| Date of the actual completion of the international search | Date of mailing of the international search report |
|---|---|
| 08 January 2002 (08.01.2002) | 29 JAN 2002 |

| Name and mailing address of the ISA/US | Authorized officer |
|---|---|
| Commissioner of Patents and Trademarks Box PCT Washington, D.C. 20231 | Tariq Hafiz  *James R. Matthews* |
| Facsimile No. (703)305-3230 | Telephone No. (703) 305-3900  701 |

Form PCT/ISA/210 (second sheet) (July 1998)